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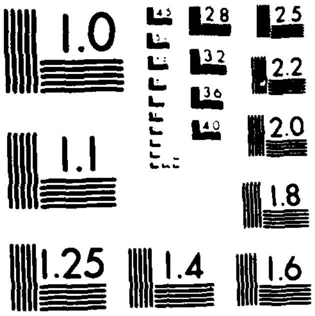

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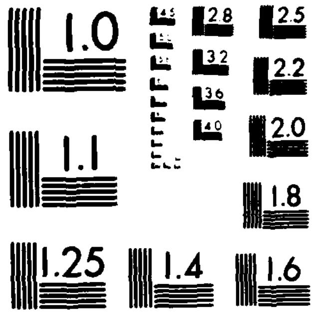

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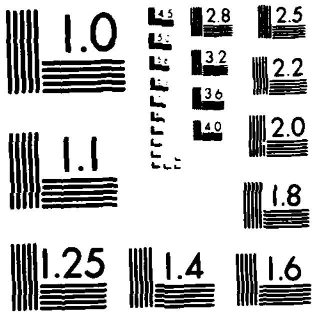

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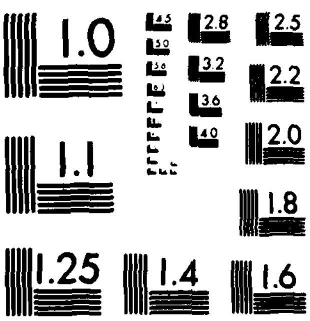

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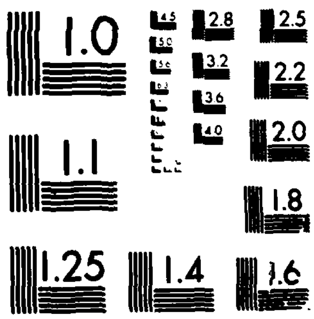

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FINAL REPORT

A PRELIMINARY ANALYSIS OF ALTERNATIVE FORECASTING TECHNIQUES FOR THE STANDARD BASE SUPPLY SYSTEM (SBSS)

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A PRELIMINARY ANALYSIS OF ALTERNATIVE FORECASTING TECHNIQUES

FOR THE STANDARD BASE SUPPLY SYSTEM (SBSS)

by

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ABSTRACT

The purpose of this research is to investigate alternative approaches to forecasting demand for expendable items in the Standard Base Supply System (SBSS). The forecasting models studied include single, double and adaptive exponential smoothing. Samples were selected from Dover AFB, Delaware and analysis of the various smoothing models was performed by a FORTRAN program written for each model. Comparison of the forecasting models was made on the basis of forecast error as measured by mean absolute deviation (MAD). The forecast error was also measured for the current forecasting model used by the SBSS. Single exponential smoothing, with small smoothing constants, proved to be the model with the lowest forecast error rate. Program activity was also studied as a possible tool to be used in demand prediction. Flying hours correlated with demand levels for some federal stock classes. Suggestions for further study are included.

ACKNOWLEDGEMENT

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I. INTRODUCTION

The USAF Standard Base Supply System (SBSS) is an automated inventory accounting system used by all Air Force bases to control their supply functions. Seppanen indicates in his technical planning study that SBSS can be categorized as a multi-item, single-echelon, continuous review inventory system with stochastic, multiple unit demands, backordering and an annual budget constraint.[15]

The SBSS was designed to facilitate the flow of materials from a multitude of sources to the base user organizations. The SBSS inventory is stocked by the arrival of material from Air Force depots, GSA, DSA as well as through local purchase. As such the SBSS is a retail organization in much the same sense as a local merchant, interfacing the wholesale level with the final consumer.

The SBSS is driven by demand action. When an item is needed, at base level, a requisition is submitted to SBSS. Typically, the request is filled from available stock. If the requested item is not available, the requisition is logged as a due-out for later filling. The request may be filled through the normal operating cycle or in some instances special orders may be required. In general, orders for resupply of the SBSS are logged as due-ins and are maintained until the material is received.

SBSS EOQ requirements computation may be divided into two components the range model and the depth model. The use of the term range model refers to the procedure employed by inventory planners to determine if an item is to be stocked. Specific criteria are available in AFM 67-1, Vol II, Part Two, to indicate whether new items should be added to the stock list or currently stocked items should be retained on the stock list.

The EOQ depth model of SBSS is used to determine how much and when to order. The depth model is based on the Economic Order Quantity (EOQ) formula:

$$EOQ = \sqrt{2DA/IP} \qquad (1)$$

Where D is the annual demand rate, A is the cost per order (currently used figure, \$5.00), I is the annual inventory carrying rate (currently used figure, 50%) and P is the item unit price. The EOQ formula balances the cost of ordering with the cost of holding inventory so that total variable cost will be minimized. Although the SBSS depth model is EOQ based only in a few instances is the exact EOQ used. A modified version of (1) is used as follows to vary the stockage level in accordance with the requisition objective.

$$EOQ_{VSO} = \sqrt{2 \cdot DDR \cdot VSO \cdot A/(I \cdot P)} \qquad (2)$$

Where A, I and P are the same as described above, DDR is the daily demand rate and VSO represents the number of days demand to be considered in the EOQ computation. The variable stockage objective (VSO) is a function of stockage priority code, number of demands in 365 days and total number of recorded demands, number of days since the first demand and the daily demand rate. Chapter 11, attachment A-16 of AFM 67-1, Vol II, Part Two contains the necessary lookup table to determine the VSO for a particular item.

In addition to the EOQ computation, which is modified by VSO, the reorder point is also an important part of SBSS. The reorder point is a combination of the order and ship time quantity (OSTQ) and safety level quantity (SLQ). The OSTQ is given by

$$OSTQ = DDR \cdot OST \qquad (3)$$

Using an average order and ship time (OST) in days based on the item source and priority. The SLQ is given by

$$SLQ = C\sqrt{3 \cdot OSTQ} \qquad (4)$$

Where C, the safety factor (is typically set to 1 which implies an 84% service effectiveness) and 3 has been historically determined as the lead time demand variance/mean ratio. The reorder point (RP) is then given by

$$RP = OSTQ + SLQ \qquad (5)$$

The requisition objective (RO) is the maximum desired inventory position and is given by

$$RO = INT(EOQ_{VSO} + OSTQ + SLQ + 0.999) \qquad (6)$$

Notice that each of the three variables included in the requisition objective computation are to some extent a function of the daily demand rate. In essence the DDR is the forecast measurement for the SBSS. Unless accurate estimates are available for the DDR considerable errors may result.

Each time a particular item is demanded the DDR is revised. SBSS maintains the cumulative recurring demand (CRD) and the date of first demand (DOFD). Each time an item is demanded, the number of units requisitioned is added to the CRD. The revised DDR is then calculated as

$$DDR = CRD/MAX(180, \text{Current Date} - DOFD) \qquad (7)$$

A minimum of 180 days usage is assumed so as not to overstock items that have just been added to the stockage list.

In addition to these routine revisions of the DDR, the CRD and DOFD are adjusted at six month intervals so as to reflect the most recent usage data. The adjustments are as follows:

$$CRD = DDR \cdot MIN(365, \text{Current Date} - DOFD) \qquad (8)$$

$$DOFD = MAX(DOFD, \text{Current date} - 365) \qquad (9)$$

These adjustments assure that the DDR computation is based on at most the past 540 days demand history. The net effect of this adjustment is to convert the forecasting model to a modified exponential smoothing with a variable smoothing parameter. Seppanen states that during the six month intervals between adjustments, new demands enter the forecast with a smoothing constant

$$\alpha = N/(365+N) \qquad (10)$$

Where N is the number of days since the last adjustment.[15]

This research is concerned with the forecasting model in the SBSS. It is not clear that the current DDR computation provides the best approach to estimating demand. Alternative approaches to forecasting which were considered in this study are limited to consumable supplies. The AFLMC, however intends to review forecasting approaches for reparables as well as consumable items.

II. OBJECTIVES

This research is the first activity of a multiphase project to study demand forecasting procedures in the SBSS. The primary objectives of this study is to investigate alternative approaches to demand forecasting for SBSS. The forecasting models which may lead to improvement in estimating DDR will be studied in detail in later phases of the project. The criteria for recommending forecasting models for further study is based on the level of forecast error. It was decided that the mean absolute deviation (MAD) would provide an acceptable measure of forecast error to be used in comparing alternative models.

A secondary objective is to analyze, to the extent possible, the use of program activity (flying hours, sorties, etc.) as a demand prediction tool. Although some studies have been conducted, it is not clear as to how program activity can be incorporated into demand prediction procedures.

In this study analysis is limited to expendable (consumable) inventory items. The data analyzed are from Dover AFB, Delaware, for a one year period from April 1978 through March 1979.

III. METHODOLOGY

In order to select appropriate forecasting models for a particular situation careful consideration must be given to the underlying characteristics of the organization. In many instances these characteristics may rule out some potential forecasting approaches and allow more detailed analysis of the

practical techniques. Such is the case with the SBSS. The typical base may stock 20,000 or more items and demand history is available for at most 540 days. The sheer number of items for which forecasts must be made would rule out forecasting models which require extensive computations. In addition the available demand history of approximately 1½ years also precludes the use of several advanced statistical techniques. For these reasons it was decided that, as an overall approach, time series analysis (decomposition), econometric methods, and correlation and regression analysis were inappropriate for consideration.[13,18] Correlation and regression analysis will be considered for only a small portion of items when program activity is studied.

The distribution of demand patterns also poses an interesting problem in the SBSS. Although some research has been done on this problem there is still no concensus on the appropriate distribution.[11, 16] This should not be surprising if one considers the number of bases and the difference in mission from one base to another. Although the demand distribution is unknown one can get a feel for the forecasting problem from a look at selected item histories as presented in Table 1 below.

TABLE 1

MONTHLY DEMAND FOR EIGHT SELECTED ITEMS IN FEDERAL STOCK CLASS 28, APRIL 1978 - MARCH 1979, DOVER AFB

Month	Item							
	1	2	3	4	5	6	7	8
A	1	0	3	0	1	0	0	0
M	1	0	4	0	7	303	6	12
J	0	0	3	0	3	190	6	0
J	0	0	5	0	11	120	6	0
A	0	1	0	0	11	51	6	0
S	2	0	7	1	2	180	14	12
O	0	0	9	0	12	343	20	0
N	0	4	4	0	3	0	0	12
D	3	0	6	0	3	250	0	0
J	3	0	3	0	11	542	6	0
F	0	0	2	0	3	12	6	8
M	1	0	4	0	4	45	6	0

The agreement among analysts familiar with this problem is strong that demand patterns are at best erratic. Cohen summarizes the situation best by posing the question, what is 30 days supply of an item with 3 demands in the last 2 years?[6]

One might raise the question of what forecasting techniques fit the situation described above which have not been ruled out already. The models left for consideration include both moving averages and exponential smoothing. The current SBSS forecasting model is a mixture of these techniques. It is a moving average in the sense that the DDR is a quotient of cumulative demands over time divided by the length of time for which these demands were accumulated. It includes exponential smoothing by the manner in which updates to CPD and DOFD are performed. Although the net effect of the current SBSS is a "hybrid" of moving averages and exponential smoothing, it is not apparent that this approach provides the best estimate of future demand. In short an approach to forecasting which reduces forecast error should provide a more accurate estimate of future demand and result in improved performance for the SBSS. The techniques which are considered in this study are single exponential smoothing, double exponential smoothing, adaptive exponential smoothing and moving averages.

The criteria for comparison of the various forecasting techniques will be based on their accuracy as measured by forecast error. The most commonly used measures of forecast error are the mean squared error (MSE) and the mean absolute deviation (MAD). Although the MSE is more tractable for statistical analysis, it's giving additional penalty to large errors make it less attractive. The most straightforward measure of error is MAD since it treats over estimates and under estimate equally by taking the magnitude of error, regardless of sign and averaging it.[1]

In addition to the measurement of forecast error for the various techniques, it is desirable to analyze the impact of the potential models on the entire system. Feeney and Sherbrooke point out that optimization on an item basis is short sighted and that a systems approach must be used to evaluate overall impact on the system.[7] In order to accomplish this analysis, the EOQ Federal Simulation Model (FEDSIM) will be used to assess the overall impact of proposed models when possible. FEDSIM is a model of SBSS and includes options to test the impact of changes within the supply system. At present an option is available to test single exponential smoothing models.

Some research has already been conducted to study the potential use of program activity as a demand prediction tool.[6, 9, 10] In general these studies have been focused at the wholesale level rather than the base level. Also these studies have been performed on reparable items as opposed to the expendable items which will be studied here. Correlation and regression analysis will be used to explore the use of program activity as a potential demand prediction tool.

The data analyzed in the current study were selected from Dover AFB, Delaware, for a one year period from April 1978 to March 1979. Units demanded monthly were tabulated from the transaction history file providing 12 data points for each selected item. The major portion of this study, evaluating alternative forecasting models, was accomplished using four samples of 200 items each from selected federal stock classes. The selected stock classes were 28, 47, 59, and 66.

In the study of program activity the monthly demand levels as well as flying hours, sorties and aircraft population from Dover AFB, Delaware, for the same time period as above were used. Samples of 200 items each were selected from federal stock classes 15, 16, 28, 29, 31 and 47.

Before any analysis was begun the data were scanned in order to detect potential outliers. The data displayed in Table 1 is representative of the demand patterns present. Only one item had an obvious outlier which was discarded from the analysis thus leaving only 199 items in federal stock class 47. In that case there were eleven months in which zero units were demanded but in one month 6,160 units were requested. This item was dropped from the sample as a potential data entry error.

IV. COMPARISON OF FORECASTING MODELS

Once the data were selected for analysis the testing of the various models was performed by developing a FORTRAN program for each technique. The programs were designed to measure the forecast error for the last ten periods, using the first two periods for initialization of the model. Since each forecasting model was tested using the same data, comparisons of their accuracy may be based on the level of forecast error. The forecast error for prospective models as well as the current SBSS forecasting model are presented in Table 2. Statistics for the several models are placed into Table 2 to facilitate comparison of the models. A detailed description of each model and analysis of results follows.

Single exponential smoothing is one of the simplest, and perhaps most popular, forecasting techniques applied to multi-item inventories.[2,13,16] It is a form of weighted average designed to smooth random variations in demand by averaging the most recent forecast with the most recent actual demand

TABLE 2

MEAN ABSOLUTE DEVIATION FOR ALTERNATIVE FORECASTING MODELS AND SBSS BY FEDERAL STOCK CLASS

	FEDERAL STOCK CLASS				
MODEL	28	47	59	66	AVERAGE
Single Exponential Smoothing					
$\alpha = .1$	3.51	3.29	.60	1.12	2.13
$\alpha = .2$	3.72	3.46	.63	1.15	2.24
$\alpha = .3$	3.83	3.62	.65	1.18	2.32
$\alpha = .4$	3.95	3.78	.67	1.22	2.41
$\alpha = .5$	4.03	3.90	.68	1.25	2.47
Double Exponential Smoothing					
$\alpha = .1$	3.82	3.52	.63	1.16	2.28
$\alpha = .2$	4.14	3.91	.70	1.26	2.50
$\alpha = .3$	4.36	4.19	.74	1.35	2.66
Adaptive Exponential Smoothing					
Chow					
Initial $\alpha = .1$	3.82	3.48	.63	1.17	2.27
Initial $\alpha = .2$	4.03	3.91	.69	1.28	2.48
Trigg and Leach					
Initial $\alpha = .1$, $\beta = .2$	3.73	3.69	.60	1.22	2.31
Moving Average 3-Month	4.28	4.87	.71	1.35	2.80
SBSS	3.59	3.72	.70	1.35	2.34

experienced. The forecast for period t (F_t) is given by

$$F_t = \alpha X_{t-1} + (1-\alpha) F_{t-1} \tag{11}$$

Where X_{t-1} is the actual demand in the prior period and α is the smoothing constant. The smoothing constant represents the weight given to the most recent actual demand data and is in a range $0 < \alpha < 1$. The selection of the smoothing constant for a particular set of items is performed through trial and error. Typically a common set of data is used to test the forecasting accuracy with alternative values of the smoothing constant. The forecast error is measured for each set of forecasts and the superior smoothing constant is determined. Forecast errors reported in Table 2 were measured as follows:

$$MAD = \frac{\sum |X_t - F_t|}{n} \tag{12}$$

where the error measurement MAD is determined for n periods. In each federal stock class the overall measure of error was determined by averaging the MAD for all items in the group. For example in federal stock class 66, the MAD for the 200 items using an $\alpha = .1$ was 1.12, an $\alpha = .2$ was 1.15 and so forth. The average forecast error for all four groups using an $\alpha = .1$ was 2.13, an $\alpha = .2$ was 2.24 and so on.

For the samples studied it is clear that the best smoothing constant is $\alpha = .1$ since this value gives the lowest forecast error in each of the four samples. The general pattern indicated is that as one increases the smoothing constant and the forecast error increases. This finding that small smoothing constants are preferable for SBSS data is consistent with the research reported in references 8, 11, and 20.

In order to forecast using single exponential smoothing a limited amount of information is required. Technically one needs only an initial forecast, an initial measurement of actual demand and a smoothing constant. The only data that need be retained to continue forecasting using single exponential smoothing are the forecast and actual demand for the preceding period. In this study the models were initialized by using the first month's actual demand as the forecast for the second month, then forecasts were made for the last ten months.

Double exponential smoothing is an extension of single smoothing and is typically applied to items that exhibit a trend pattern.[13,18] Since both single and double smoothed values lag actual data when a trend exists, the difference between the single and double smoothed values can be added to the single smoothed values and adjusted for trend. This approach is also referred to as linear exponential smoothing. The calculations required for double smoothing as presented by Makridakis and Wheelwright are as follows:[13]

$$S'_t = \alpha X_t + (1-\alpha) S'_{t-1} \qquad (13)$$

$$S''_t = \alpha S'_t + (1-\alpha) S''_{t-1} \qquad (14)$$

where S_t and S_t are single and double smoothed values respectively.

$$a_t = 2\, S'_t - S''_t \qquad (15)$$

$$b_t = \alpha/(1-\alpha) \cdot (S'_t - S''_t) \qquad (16)$$

and the forecast for period t+1 is

$$F_{t+1} = a_t + b_t \qquad (17)$$

In order to use this approach only three data values and a smoothing constant are required. Initialization of this model was accomplished by setting S'_2 and S''_2 equal to X_1, the actual demand in the first month. Then forecasts were prepared for the last ten months using three different smoothing constants

α =.1, α =.2 and α =.3. The results presented in Table 2 demonstrate that as α is increased the forecast error tends to also rise. Furthermore the double smoothing model produced a higher degree of forecast error than did single exponential smoothing for these four samples. In none of the four groups was double smoothing superior to single smoothing. This may also indicate that as a general rule trend does not exist in SBSS items. Due to the erratic nature of demand patterns, it is not surprising that adjusting for trend did not reduce forecast error. With the variation present in SBSS items there may well be more than random variability in demand data. In order to test this phenomena adaptive models will be considered.

When forecast are required for several thousand items as in the SBSS it seems reasonable that more than one smoothing parameter should be used. That is the weight given to most recent data should be greater when a persistent demand pattern exists and should be reduced when highly erratic demand patterns occur. The cost associated with studying each item separately to determine the appropriate smoothing constant to minimize forecast error would be extremely high, whether single or double smoothing is to be used. It was hoped that some criteria such as essentiality codes could be used to at least study groups of items but these data were not available during the term of this research. Adaptive forecasting models were studied since they are self-regulating based on forecast error and thus bypass the problems of item by item analysis and stratification.

The first adaptive model tested in this study was developed by Chow in 1965.[5,13,18] The Chow model is designed to allow the smoothing constant to adapt in small increments in order to minimize forecast error. The model assumes that the time ordered data contains all or some of the following:

trend; cyclical movements, including seasonal; and random variation. The equations necessary for employing this method are as follows:

$$S_t = \alpha_t X_t + (1-\alpha_t)S_{t-1} \qquad (18)$$

$$b_t = \alpha_t (S_t - S_{t-1}) + (1-\alpha_t)b_{t-1} \qquad (19)$$

and the forecast is

$$F_{t+1} = S_t + \frac{(1-\alpha_t)b_t}{\alpha_t} \qquad (20)$$

At the outset the forecaster is required to have initial values for S, b and $_t$ as well as an increment to be used in changing the smoothing parameter. Initialization employed in this study was to set S_1 equal to X_1 and b_1 equal to zero. The forecast for the second month (F_2) was set equal to X_1 and therefore comparable to the start-up values for single and double smoothing models described above. Since small values of the smoothing parameter provided best results in the models already studied the Chow model was tested with initial values of $\alpha_t=.1$ and $\alpha_t=.2$. The increment for changing the smoothing constant was set at .05. Overall limits for the smoothing constant were set so that it remained in the range $.05 \leq \alpha_t \leq .95$.

The revision of the smoothing constant is the unique feature of Chow's model. At each time period three values of α must be considered; a "nominal" value, a low value and a high value. The forecast for the next period is always derived using the "nominal" value but dependent on the forecast error measured in the current period the "nominal" value for next period may either increase or decrease by the amount of the pre-determined increment. This allows the smoothing constant to respond to changes in demand patterns but at the same time limits its responsiveness to the amount of the increment.

In comparison to single and double smoothing models the Chow model requires more recordkeeping so that the smoothing constant can be revised. Since in each time period three forecasts must be made, the necessary data to continue the procedure must be available. One might note that in addition to the current smoothing value and the three forecasts for the last period, three values must be kept for both S_t and b_t. Thus it is clear that the overhead for maintaining the Chow model exceeds that for previously described models.

The results from the Chow model are presented in Table 2. The lowest forecast error was obtained when the initial smoothing constant was set at .1. The average figure of 2.27 indicates that this model performed about as well as the double smoothing model but was not superior to single smoothing.

One other adaptive model was tested, the Trigg and Leach model.[13,18] It differs from the Chow model by using the ratio of two forecast error measurements to calculate the smoothing constant. The equations required in the model are given by Makridakis and Wheelwright[13] as follows:

$$F_{t+1} = \alpha_t X_t + (1-\alpha_t)F_t \qquad (21)$$

Where

$$\alpha_{t+1} = \left|\frac{E_t}{M_t}\right| \qquad (22)$$

$$E_t = \beta e_t + (1-\beta)\, E_{t-1} \qquad (23)$$

$$M_t = \beta |e_t| + (1-\beta) M_{t-1} \qquad (24)$$

$$e_t = X_t - F_t \qquad (25)$$

β is a constant used to smooth the forecast error in the equations for E_t, the smoothed error, and M_t, the absolute smoothed error. It is set in the range $0 < \beta < 1$ and in the current study β was set equal to .2. Forecasting was begun by setting E_1, M_1 and e_1 to zero and F_2 was set equal to X_1, making

initialization comparable to the previously discussed models. The initial value of α was set equal to .1 and this value was used until the adaptive feature of the model could take over. One should recognize that the calculation of α_{t+1} does not begin until the actual demand is less than the forecast since E_t and M_t will be equal until e_t takes on a negative value. The forecast error resulting from this model is shown in Table 2. The forecast error did not prove less than in previously tested models, but was comparable to the Chow model and the double smoothing model.

The data which must be kept to employ the Trigg and Leach model includes the forecasted value, the smoothed error, the absolute smoothed error and the value of α_{t+1}. β may be included in programming as a constant and of course actual demand (X_t) must be kept as in any forecast model. Less storage space is required for the Trigg and Leach model than for the Chow model but of course more data is required than for the single or double smoothed models.

In addition to the smoothing models described above, moving averages were considered. Due to limited available data only a 3 month moving average was considered. Of all the models tested it is perhaps the simplest. The forecast for a particular period is simply the average of the last 3 periods actual demand.

$$F_{t+1} = (X_t + X_{t-1} + X_{t-2})/3 \qquad (26)$$

Since only 12 data points were available, forecast for the last nine months were derived. Forecast error was measured by MAD as in the other models tested. This approach provided the highest degree of forecast error of any of the models studied as is indicated in Table 2.

One question that remains to be addressed is a comparison of the forecast error in the current forecasting model employed by SBSS. A FORTRAN program was written to forecast the last ten months of the sample period and measure its forecast error. The results are presented in Table 2. Single smoothing with an α =.1 was the only model which had a lower forecast error in each sample. But from the average of all four groups it appears that forecast error can be reduced by other techniques as well. Additional study through simulation is required to assess the overall impact of forecasting on the SBSS.

It is interesting to note that in the test of forecasting models the forecast error differ substantially between groups. It is not surprising that forecast error varies with item activity as was reported by Kaplan.[12] It would appear that the federal stock classes selected for this study provide a cross section of SBSS items.

V. SIMULATION RESULTS

At present single exponential smoothing is the only forecasting model which could be tested using the FEDSIM model and compared to SBSS data. The default option of FEDSIM was used to select a stratified sample of 5000 items from the demand data on Dover AFB, Delaware for a one year period April 1978 - March 1979. The single exponential smoothing option was run for α =.1 and α =.2 with quarterly forecasts. The year end results are shown in Table 3 along with the current SBSS forecasting results.

TABLE 3

SBSS SIMULATION RESULTS USING THE CURRENT FORECASTING MODEL AND SINGLE EXPONENTIAL SMOOTHING

Effectiveness Measure	Current System	Single Smoothing $\alpha = .1$	Single Smoothing $\alpha = .2$
Line Item Fill Rate (%)	85.40	84.43	83.86
Net Line Item Fill Rate (%)	89.68	88.77	87.73
Units Fill Rate (%)	84.60	82.61	80.83
Net Units Fill Rate (%)	86.75	85.06	82.85
Avg. On-Hand Inventory ($)	772,033	754,032	721,855
Avg. On-Order Inventory ($)	245,638	244,193	236,933
Avg. Due-Out Inventory ($)	35,474	37,563	38,910

In comparing these results consider the change in the net line item fill rate and the average on-hand inventory level. The net line item fill rate is a measure of effectiveness considering only items which are stocked by SBSS. This rate is lower in both simulations of single smoothing than for the current system, however, the average on-hand inventory is reduced as well. The fact that lower inventory levels reduce issue effectivenss is not surprising. The decision that must be made is whether the reduction in issue effectivenss is worth the savings which result. For example the simulation of single smoothing with $\alpha = .1$ shows roughly a one percent reduction in the net line item fill rate and approximately a $28,000 reduction in the average on-hand inventory. Keeping in mind that this simulation is for only 5,000 items at one base, the potential savings Air Force wide would be a significant amount if this relationship exists as a general rule. Clearly a one year simulation at one base does not provide

sufficient evidence to reach an optimal decision. If these patterns are found to exist on other bases, the trade-off between issue and asset effectiveness must be considered if the SBSS forecasting model is to be revised.

VI. PROGRAM ACTIVITY AND DEMAND PREDICTION

It is realized that program activity (flying hours, sorties, etc.) has limited potential as a general approach to demand prediction. That is, only a small portion of items in SBSS are likely to be directly affected by program factors. In addition prior studies have focused on the wholesale rather than base level to consider the effects of program activity on the demand for selected reparable items.[6,9,10,16] In this study the demand activity of expendable items from selected federal stock classes were analyzed along with program factors. Units demanded monthly in federal stock classes 15, 16, 28, 29, 31, and 47, for samples of 200 items in each class, were determined. Monthly data were also obtained for the following program factors: flying hours, sorties flown and possessed aircraft. Statistical analysis was then performed using the stepwise regression program available in the Honeywell 6000 timesharing system. Measures of correlation between program factors and demand levels are shown in Table 4.

TABLE 4

CORRELATIONS BETWEEN PROGRAM FACTORS AND UNITS DEMANDED BY FEDERAL STOCK CLASS

FEDERAL STOCK CLASS	PROGRAM FACTOR		
	FLYING HOURS	SORTIES FLOWN	POSSESSED AIRCRAFT
15	-.620*	-.479	.079
16	-.297	-.452	.315
28	-.155	.045	-.618*
29	-.633*	-.619*	.092
31	-.627*	-.238	-.372
47	-.427	-.283	.138

*Significant at .05 level.

In three of the federal stock classes flying hours correlate significantly with units demanded. This finding is consistent with the prior studies on reparable items.[9,10] However, it is still not clear as to how these results can be used to predict demand on an item basis at base level. Each of the significant correlation coefficients are negative which indicates an inverse relationship between the program factors and units demanded. One possible explanation for this is that during extensive program activity some maintenance is postponed thereby creating a lag in parts demand. Available data prevented further study to determine if such a lag actually exists.

Multiple regression equations were also determined for units demanded in each federal stock class using program factors as independent variables. Analysis of the residuals showed high errors in prediction and that the use of more than one program factor did not improve the prediction of demand levels. In short no useful results were obtained from the regression analysis, perhaps due to the way in which demand was measured. It appears that the use of program activity in predicting the demand for expendable items is still questionable.

VI. RECOMMENDATIONS

The purpose of this research was to investigate alternative approaches to demand forecasting for the SBSS. From the measurement of forecast error (MAD) single exponential smoothing, with small smoothing constants, emerged as the technique with the lowest error rate. In addition simulation results indicated that potential savings exist through a reduction of average inventory. It is clear that these findings can only be considered preliminary and that the analysis of larger samples from several bases will be required before substantive conclusions can be reached.

The double exponential smoothing model and the adaptive models tended to produce about the same level of forecast error. Since it is not likely that all items have a trend pattern, perhaps adaptive models should be considered as the second choice for further study. The time period in the present study may have been too short to allow the adaptive models to overcome the initialization conditions employed. Analysis of adaptive models for a longer time period may be required to adequately test its forecasting performance. However, considering the large number of items to be forecast at each base, the additional data requirements for adaptive models must be studied carefully.

Another consideration for further study is the stratification of items into homogenous groups in order to reduce forecast error. This grouping might be on the basis of item activity (high, medium and low volume) or item essentiality. Given the large number of items it would appear that this approach could reduce forecast error. This does not necessarily require completely different approaches to forecasting. For example the general approach to forecasting might be single exponential smoothing but with different smoothing constants for each strata.

Due to the limited data base available, monthly demand data were studied. For many items a large number of months were observed to have zero demands. Further study of demand data may be enhanced by the analysis of quarterly rather than monthly data. Given the large number of items at each base and the available computer facilities, as a practical matter quarterly forecast may be preferable.

In regard to program activity as a demand prediction tool for expendable items, this study does not provide any substantive conclusions. Although flying hours were correlated to demand level for some federal stock classes, the inverse relationship present could not be adequately explained. Since program activity is likely to be used for a very small number of items, further study should concentrate on a well defined group of items.

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The purpose of this research is to investigate alternative approaches to forecasting demand for expendable items in the Standard Base Supply System (SBSS). The forecasting models studied include single, double and adaptive exponential smoothing. Samples were selected from Dover AFB, Delaware, and analysis of the various smoothing models was performed by a FORTRAN program written for each model. Comparison of the forecasting models was made on the basis of forecast error as measured by mean absolute deviation (MAD). The forecast error was also measured for the current forecasting model used by the SBSS. (CONTINUED)

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ITEM #20, CONTINUED: Single exponential smoothing, with small smoothing constants, proved to be the model with the lowest forecast error rate. Program activity was also studied as a possible tool to be used in demand prediction. Flying hours correlated with demand levels for some Federal stock classes. Suggestions for further study are included.